

Supplementary Material to:

Incremental Process for Reliable SLAM under Constrained Optimization Formulation

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Abstract—This is the supplementary material to the paper entitled “Incremental Process for Reliable SLAM under Constrained Optimization Formulation”. Some fundamentals about $SO(3)$ and the linearization of the constrained SLAM formulation are presented in this documentation.

I. PRELIMINARIES ON $SO(3)$ GROUP

A. A Brief Introduction to $SO(3)$ Group

The definition of special orthogonal group ($SO(3)$ group) is the set of valid rotation matrices

$$SO(3) \stackrel{\text{def}}{=} \{\mathbf{R} \in \mathbb{R}^{3 \times 3} | \mathbf{R}\mathbf{R}^T = \mathbf{I}, \det(\mathbf{R}) = 1\}.$$

The Lie algebra of $SO(3)$ (denoted by $\mathfrak{so}(3)$), is usually referred as a set of skew-symmetric matrices which can be identified by an element in \mathbb{R}^3 . Denote the skew-symmetric matrix associated with $\Theta \in \mathbb{R}^3$ as $[\Theta]_{\times} \in \mathfrak{so}(3)$, then

$$[\Theta]_{\times} = \begin{bmatrix} 0 & -\theta_3 & \theta_2 \\ \theta_3 & 0 & -\theta_1 \\ -\theta_2 & \theta_1 & 0 \end{bmatrix} \in \mathfrak{so}(3).$$

For each rotation \mathbf{R} , there is an axis-angle representation Θ . The rotation matrix \mathbf{R} and its corresponding axis-angle Θ are connected by exponential mapping $\text{Exp}(\cdot)$ and logarithm mapping $\text{Log}(\cdot)$ as below.

$$SO(3) \ni \mathbf{R} = \text{Exp}(\Theta) = \mathbf{I} + \frac{[\Theta]_{\times}}{\|\Theta\|} \sin \|\Theta\| + \frac{[\Theta]_{\times}^2}{\|\Theta\|^2} (1 - \cos \|\Theta\|)$$

$$\mathbb{R}^3 \ni \Theta = \text{Log}(\mathbf{R}) = \frac{\theta}{2 \sin \theta} \begin{bmatrix} r_{32} - r_{23} \\ r_{13} - r_{31} \\ r_{21} - r_{12} \end{bmatrix}$$

where $\theta = \cos^{-1}(\frac{\text{trace}(\mathbf{R})-1}{2})$, $r_{ij} \in \mathbb{R}$ is the ij -th elements of the rotation matrix \mathbf{R} .

The BCH formula to incorporate the perturbation on $SO(3)$ into the axis-angle space is presented as,

$$\text{Exp}(\Theta_1) \cdot \text{Exp}(\Theta_2) \approx \begin{cases} \text{Exp}[\mathbf{J}_r^{-1}(-\Theta_2) \cdot \Theta_1 + \Theta_2] & \Theta_1 \rightarrow \mathbf{0} \\ \text{Exp}[\Theta_1 + \mathbf{J}_r^{-1}(\Theta_1) \cdot \Theta_2] & \Theta_2 \rightarrow \mathbf{0} \end{cases}$$

where $\mathbf{J}_r(\cdot)$ is the so-called right-hand Jacobian given by

$$\mathbf{J}_r(\Theta) = \mathbf{I} - \frac{1 - \cos \|\Theta\|}{\|\Theta\|^2} [\Theta]_{\times} + \frac{\|\Theta\| - \sin \|\Theta\|}{\|\Theta\|^3} [\Theta]_{\times}^2.$$

If $\Theta = \mathbf{0}$, $\mathbf{J}_r(\Theta) = \mathbf{I}$.

An identity as below derived from the adjoint operation of $SO(3)$ is

$$\mathbf{R} \cdot \text{Exp}(\Theta) \cdot \mathbf{R}^T = \text{Exp}(\mathbf{R}\Theta).$$

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B. Properties

Some properties for $SO(3)$ group are listed as below.

$$[\Theta_1]_{\times} \cdot \Theta_2 = -[\Theta_2]_{\times} \cdot \Theta_1, \quad \forall \Theta_1, \Theta_2 \in \mathbb{R}^3$$

$$\mathbf{R} \cdot [\Theta]_{\times} \cdot \mathbf{R}^T = [\mathbf{R}\Theta]_{\times}, \quad \forall \Theta \in \mathbb{R}^3, \mathbf{R} \in SO(3)$$

$$\text{Exp}(\Theta) \approx \mathbf{I} + [\Theta]_{\times} + \frac{1}{2}[\Theta]_{\times}^2, \quad \text{if } \mathbb{R}^3 \ni \Theta \rightarrow 0$$

$$\mathbf{R} \cdot \text{Exp}(\Theta) = \text{Exp}(\mathbf{R}\Theta) \cdot \mathbf{R}, \quad \forall \Theta \in \mathbb{R}^3, \mathbf{R} \in SO(3)$$

II. LINEARIZATION OF THE CONSTRAINED SLAM FORMULATION

A. Linearization of the Translational Equation

The linearization of the translational equation can be attained by firstly linearizing terms like

$$\mathbf{F}_c = [\prod_{i=1}^m \mathbf{R}_i] \mathbf{y} \quad (\mathbf{R}_i \in SO(3), \mathbf{y} \in \mathbb{R}^3)$$

then collecting the linearized terms together to obtain a full linearized version.

Let $\Omega_m^n = \prod_{i=m}^n \mathbf{R}_i$, then \mathbf{F}_c can be written as

$$\mathbf{F}_c = [\prod_{i=1}^m \mathbf{R}_i] \mathbf{y} = \Omega_1^{j-1} \cdot \mathbf{R}_j \cdot \Omega_{j+1}^m \mathbf{y}.$$

For \mathbf{R}_j and \mathbf{y} , add a perturbation on their current estimate $\check{\mathbf{R}}_j$ and $\check{\mathbf{y}}$ respectively, then approximate the rotational perturbation with its second-order approximation, which results

$$\mathbf{R}_j = \check{\mathbf{R}}_j \cdot \text{Exp}(\Theta_j) \approx \check{\mathbf{R}}_j \cdot (\mathbf{I} + [\Theta_j]_{\times} + \frac{1}{2}[\Theta_j]_{\times}^2)$$

$$\mathbf{y} = \check{\mathbf{y}} + \mathbf{y}_m$$

where $\Theta_j \rightarrow \mathbf{0}$, $\mathbf{y}_m \rightarrow \mathbf{0}$.

By Taylor expansion, at point $\mathbf{y}_m = \mathbf{0}$, $\Theta_j = \mathbf{0}$ ($j = 1, \dots, m$), we have

$$\mathbf{F}_c = \mathbf{F}_c|_0 + \frac{\partial \mathbf{F}_c}{\partial \mathbf{y}_m}|_0 \mathbf{y}_m + \sum_{j=1}^m \frac{\partial \mathbf{F}_c}{\partial \Theta_j}|_0 \Theta_j + \mathbf{o}$$

$$\begin{aligned} \frac{\partial \mathbf{F}_c}{\partial \Theta_j}|_0 &= \frac{\partial}{\partial \Theta_j} \{ \Omega_1^{j-1} \cdot \check{\mathbf{R}}_j \cdot (\mathbf{I} + [\Theta_j]_{\times} + \frac{1}{2}[\Theta_j]_{\times}^2) \cdot \Omega_{j+1}^m \mathbf{y} \}|_0 \\ &= \frac{\partial}{\partial \Theta_j} \{ \Omega_1^{j-1} \cdot \check{\mathbf{R}}_j \cdot [\Theta_j]_{\times} \cdot \Omega_{j+1}^m \mathbf{y} \}|_0 \\ &= \frac{\partial}{\partial \Theta_j} \{ -\Omega_1^{j-1} \cdot \check{\mathbf{R}}_j \cdot [\Omega_{j+1}^m \mathbf{y}]_{\times} \cdot \Theta_j \}|_0 \\ &= -\Omega_1^{j-1} \cdot \check{\mathbf{R}}_j \cdot [\Omega_{j+1}^m \mathbf{y}]_{\times} |_0 \\ &= -\check{\Omega}_1^{j-1} \cdot \check{\mathbf{R}}_j \cdot [\check{\Omega}_{j+1}^m \check{\mathbf{y}}]_{\times} \\ &= -\check{\Omega}_1^j [\check{\Omega}_{j+1}^m \check{\mathbf{y}}]_{\times} \end{aligned}$$

$$\left. \frac{\partial \mathbf{F}_c}{\partial \mathbf{y}_m} \right|_0 = \frac{\partial}{\partial \mathbf{y}_m} \left\{ \left[\prod_{i=1}^m \mathbf{R}_i \right] (\check{\mathbf{y}} + \mathbf{y}_m) \right\} \Big|_0 = \left[\prod_{i=1}^m \mathbf{R}_i \right] \Big|_0 = \left[\prod_{i=1}^m \check{\mathbf{R}}_i \right] = \check{\mathbf{\Omega}}_1^m$$

$$\mathbf{F}_c \Big|_0 = \left[\prod_{i=1}^m \mathbf{R}_i \right] \mathbf{y} \Big|_0 = \left[\prod_{i=1}^m \check{\mathbf{R}}_i \right] \check{\mathbf{y}} = \check{\mathbf{\Omega}}_1^m \check{\mathbf{y}}$$

Note here we use notation $\check{\mathbf{\Omega}}_m^n = \prod_{i=m}^n \check{\mathbf{R}}_i$.

Thus, after linearization

$$\mathbf{F}_c = \check{\mathbf{\Omega}}_1^m \check{\mathbf{y}} + \check{\mathbf{\Omega}}_1^m \mathbf{y}_m - \sum_{j=1}^m \check{\mathbf{\Omega}}_1^j [\check{\mathbf{\Omega}}_{j+1}^m \check{\mathbf{y}}] \times \Theta_j + \mathbf{o}.$$

B. Linearization of the Rotational Equation

For the rotational equation, a term in the form like

$$\prod_{i=1}^m \mathbf{R}_i = \mathbf{R}_1 \mathbf{R}_2 \cdots \mathbf{R}_m = \mathbf{R}_0$$

needs to be linearized.

For each rotation \mathbf{R}_i ($i = 0, 1, \dots, m$), adding a perturbation Θ_i in the axis-angle space at its current estimate $\check{\mathbf{R}}_i$, the constraint can be written as

$$\prod_{i=1}^m [\check{\mathbf{R}}_i \mathbf{Exp}(\Theta_i)] = \check{\mathbf{R}}_0 \mathbf{Exp}(\Theta_0). \quad (1)$$

Using the identity

$$\mathbf{R} \cdot \mathbf{Exp}(\Theta) = \mathbf{Exp}(\mathbf{R}\Theta) \cdot \mathbf{R}$$

iteratively, the left-hand side of (1) becomes

$$\begin{aligned} \prod_{i=1}^m [\check{\mathbf{R}}_i \mathbf{Exp}(\Theta_i)] &= \left\{ \prod_{i=1}^m \mathbf{Exp} \left(\left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i \right) \right\} \cdot \prod_{i=1}^m \check{\mathbf{R}}_i \\ &\approx \mathbf{Exp} \left(\sum_{i=1}^m \left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i \right) \cdot \prod_{i=1}^m \check{\mathbf{R}}_i. \end{aligned}$$

Hence (1) takes the form

$$\mathbf{Exp} \left(\sum_{i=1}^m \left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i \right) \cdot \prod_{i=1}^m \check{\mathbf{R}}_i \approx \mathbf{Exp}(\check{\mathbf{R}}_0 \Theta_0) \cdot \check{\mathbf{R}}_0.$$

Let $\eta = \mathbf{Log}(\check{\mathbf{R}}_0 \cdot [\prod_{i=1}^m \check{\mathbf{R}}_i]^\top)$, then

$$\mathbf{Exp}(-\check{\mathbf{R}}_0 \Theta_0 + \sum_{i=1}^m \left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i) \cdot \mathbf{Exp}(-\eta) \approx \mathbf{I}.$$

Using BCH formula, it can be written as

$$\mathbf{Exp}(\mathbf{J}_r^{-1}(\eta) \{-\check{\mathbf{R}}_0 \Theta_0 + \sum_{i=1}^m \left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i\} - \eta) \approx \mathbf{I}.$$

The axis-angle space takes the form

$$\mathbf{J}_r^{-1}(\eta) \{-\check{\mathbf{R}}_0 \Theta_0 + \sum_{i=1}^m \left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i\} - \eta \approx \mathbf{0} \quad (2)$$

if Θ_i and η are small.

Equivalently, (2) can be written as

$$-\check{\mathbf{R}}_0 \Theta_0 + \sum_{i=1}^m \left[\prod_{j=1}^i \check{\mathbf{R}}_j \right] \cdot \Theta_i \approx \mathbf{J}_r(\eta) \eta.$$

C. Linearization of the Objective Function

The only non-linear part of the objective lies in the logarithm mapping which can be linearized as follow.

$$\begin{aligned} \mathbf{Log}(\mathbf{Z}_{R_j^i}^\top \mathbf{R}_j^i) &= \mathbf{Log}\{\mathbf{Z}_{R_j^i}^\top \check{\mathbf{R}}_j^i \cdot \mathbf{Exp}(\Theta_j^i)\} \\ &= \mathbf{Log}\{\mathbf{Exp}(\eta_{R_j^i}) \cdot \mathbf{Exp}(\Theta_j^i)\} \\ &\approx \mathbf{Log}\{\mathbf{Exp}[\eta_{R_j^i} + \mathbf{J}_r^{-1}(\eta_{R_j^i}) \Theta_j^i]\} \\ &= \eta_{R_j^i} + \mathbf{J}_r^{-1}(\eta_{R_j^i}) \Theta_j^i \end{aligned}$$

where $\eta_{R_j^i} = \mathbf{Log}(\mathbf{Z}_{R_j^i}^\top \check{\mathbf{R}}_j^i)$.

III. DISCUSSION

As mentioned in the paper, it is also possible to choose $SE(3)$ optimization techniques by considering the translational and rotational part together as $SE(3)$ transformations. The linearization on $SE(3)$ is very similar to the linearization of the rotational equation described in Section II-B. However, to generalize the implementation of pose-graph SLAM and feature-based SLAM, we stick to $SO(3)$ linearization techniques here.

It is worth mentioning that the covariance for $SE(3)$ and $SO(3)$ are slightly different. For the rotational part, the covariance are exactly the same. However for the translational part, the covariance for $SO(3)$ and $SE(3)$ are related by

$$\mathbf{R}_z \cdot \Sigma_T \cdot \mathbf{R}_z^\top = \Omega_T$$

Here \mathbf{R}_z is the rotational part of the relative pose measurement data, and Σ_T is the covariance for the translational part in $SE(3)$ while Ω_T is that in $SO(3)$. This can be examined easily by considering the translational and rotational part in $SE(3)$ separately.